# A Unified Spatial-Temporal-Spectral Learning Framework For Reconstructing Missing Data In Remote Sensing Images

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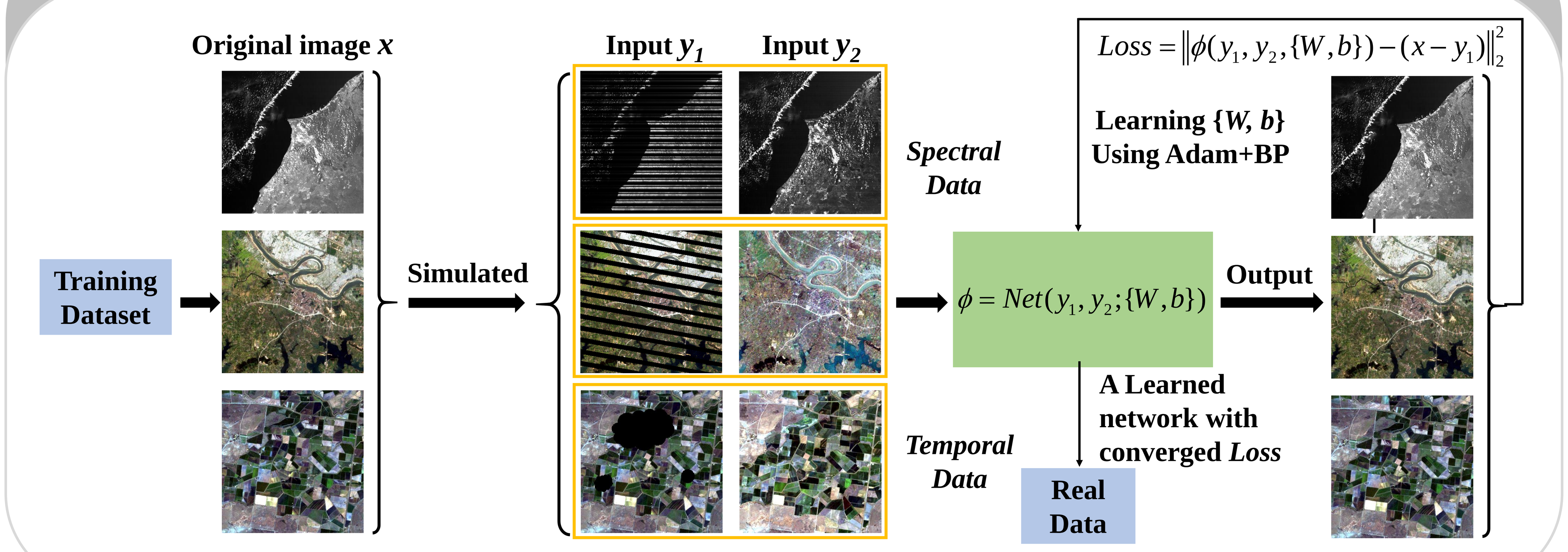
## Introduction

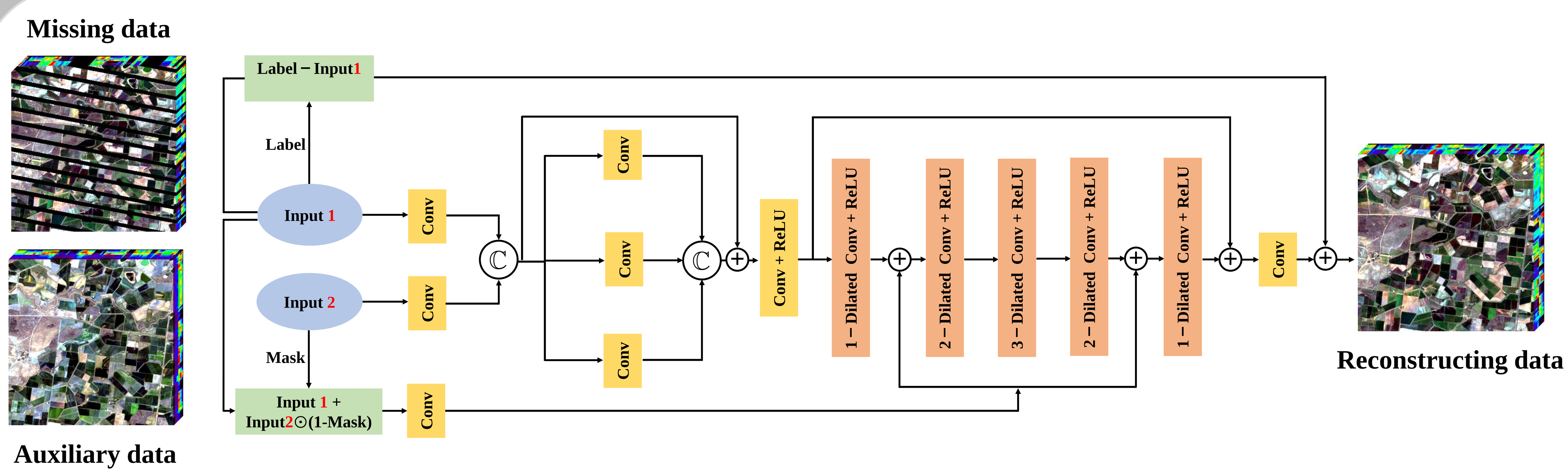
(a) Aqua MODIS band 6 (b) Landsat ETM+ SLC-off (c) QuickBird with thick cloud

Because of the satellite sensor working conditions and the atmospheric environment, remote sensing images often suffer from missing information problems, such as dead pixels and thick cloud cover. It should be stressed that, such discontinuous data cannot easily be used in the subsequent applications [1]. Therefore, missing information reconstruction is an important task in the field of remote sensing imagery processing.

## UNIFIED FRAMEWORK




## Method




**Proposed STS-CNN model. (Available Codes: https://github.com/WHUQZhang/STS-CNN)**

- **Fusion of Spatial-Temporal-Spectral Data**

In the proposed model, we input two types of data into the network, one of which is the spatial data with missing areas, and the other is the complementary information with spectral or temporal data.

- **Dilated Convolution for Larger Receptive Field Sizes**

In STS-CNN model, dilated convolutions are employed which can both enlarge the receptive field and maintain size of convolution kernel filter. More contextual information can effectively promote the restoration of degraded images.

- **Residual Learning for Deeper layers and Reducing Loss**

Compared with traditional data mapping, the spatial distribution of the residual feature maps should be very sparse, which can transfer the gradient descent process to a much smoother hyper-surface of loss [8] to the filtering parameters as below:

$$loss(\Theta) = \frac{1}{2N}\sum_{i=1}^{N}\left\| \phi(y_i^1, y_i^2, \Theta) - r_i \right\|_2^2$$

## Experiment and Result

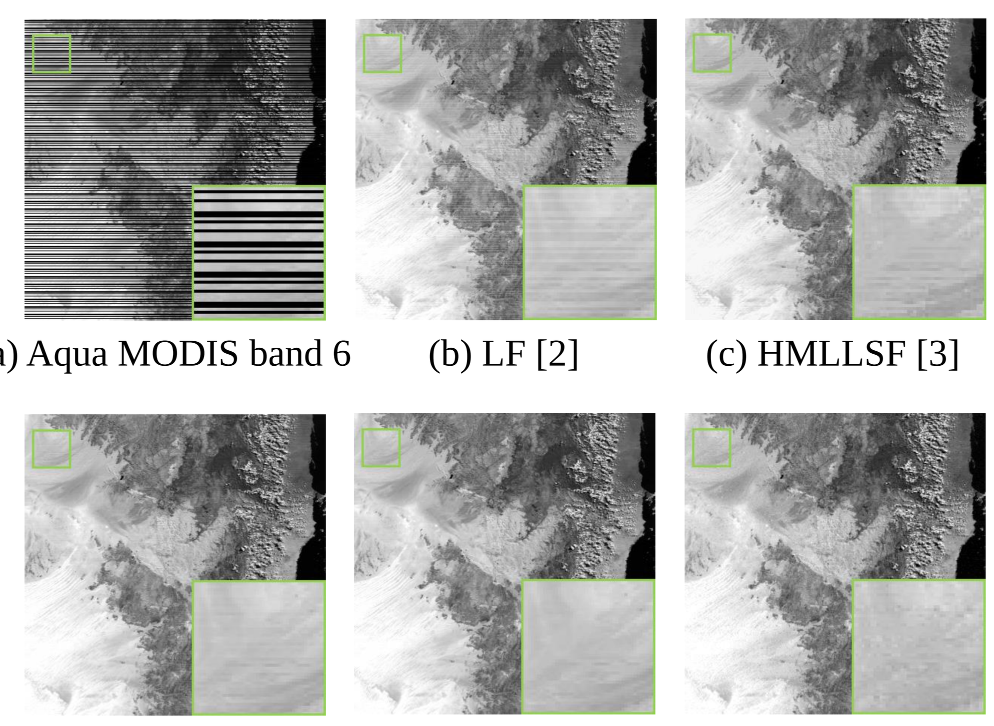
### Network Training and Testing

The proposed model was trained using the stochastic gradient descent (SGD) algorithm as the gradient descent optimization method, where the learning rate was initialized to 0.01 for the whole network. For the different reconstruction tasks, the training processes were all set to 100 epochs. After every 20 epochs, the learning rate was multiplied by a declining factor 0.1.

For the dead lines of Aqua MODIS Band 6, we selected original Terra MODIS imagery as our training dataset, since it has a high degree of similarity. For the training of the network, we chose and cropped 600 images of size 400×400×7 and set each patch size as 40×40 and stride 40. For the real dead lines of Aqua MODIS band 6, an Aqua MODIS L1B 500-m resolution image of size 400×400×7 was used in the real-data experiments.

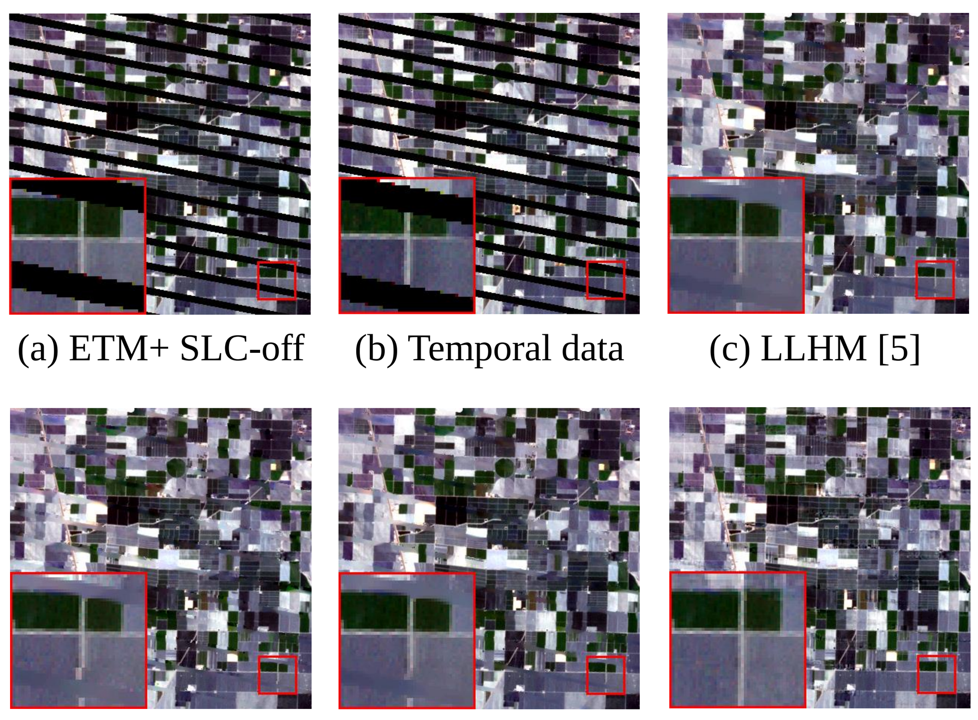
For the ETM+ SLC-off problem and the removal of thick cloud, we used 16 different temporal Landsat Thematic Mapper (TM) images from 2001.10.7 to 2002.5.4 (size of 1720×2040×6, 30-m spatial resolution) and arranged them in sets of temporal pairs. These pairs of temporal data were then cropped in each patch size as 100×100 and stride 100 as the training datasets. Two actual ETM+ SLC-off temporal images, and two temporal images with/without cloud in [9] were also tested for the real-data experiments.

### Real-data experiments



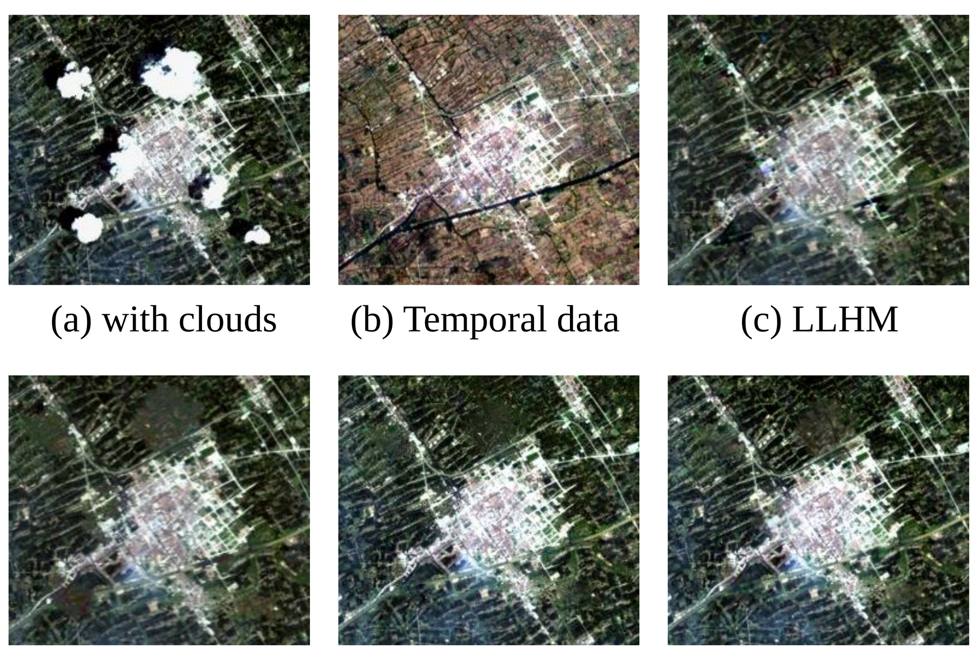
(a) Aqua MODIS band 6 (b) LF [2] (c) HMLLSF [3]
(d) WCLF [4] (e) AWTC [9] (f) Ours

▸ **Experiment 1:** Real-data missing data recovery results for the Aqua MODIS band 6 deadline image.



(a) ETM+ SLC-off (b) Temporal data (c) LLHM [5]
(d) NSPI [6] (e) WLR [7] (f) Ours

▸ **Experiment 2:** Real-data missing data recovery results for the Landsat ETM+ SLC-off image.



(a) with clouds (b) Temporal data (c) LLHM
(d) NSPI (e) WLR (f) Ours

▸ **Experiment 3:** Real-data missing data recovery results for thick clouds removal with Landsat TM temporal image.

## Conclusion

We presented a novel method for the reconstruction of remote sensing imagery with missing data, through a unified spatial-temporal-spectral framework (STS-CNN). From the perspective of non-linear expression with deep learning theory and spatial-temporal-spectral fusion, STS-CNN can jointly take advantage of auxiliary complementary data from the spatial, spectral, and temporal domains for different missing information tasks.

Although the proposed method performs well for reconstructing missing data, it still has some unavoidable limitations. Another possible strategy which will be explored in our future research like adding a priori constraint.

## References

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